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Design of arable land protection framework in the context of ecological civilisation based on hybrid optimisation algorithm

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ABSTRACT
Food security is an important foundation of national security, and the fundamental of guaranteeing national food security lies in arable land protection. In order to realize the protection of arable land in the context of ecological civilization, this paper designs a governance framework for arable land protection based on supply, empowerment, and control on the basis of the trinity of arable land protection policy of quantity, quality, and ecology, and constructs a multi-objective land use structure optimization model, and obtains a scenario prognosis for the optimal allocation of the land use structure by using a hybrid genetic algorithm. Taking County A as the specific research object, it can be seen by predicting the land use structure under the natural development scenario of County A that, relative to the status quo in 2023, the predicted share of arable land in 2050 has the largest decrease of 0.49%, and the shares of garden land, forest land, grassland and water area have all decreased, which is mainly converted into construction land (increased by 0.78%). From the Pareto frontier solution of land ecological benefit objective and economic benefit objective, three typical schemes of land use structure optimization were obtained, among which, the optimization scheme of balanced development of economy and ecology balanced economic and ecological development balanced economic development and ecological protection, and was selected as the optimization scheme of this paper. The increase of arable land area in this scheme is 0.38%, much higher than the -2.46% in the unoptimized case, which is in line with the requirement of arable land retention and can be used as a reference for further optimization of arable land protection framework.

Keywords: multi-objective optimization; hybrid genetic algorithm; local search; cropland protection

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1. Introduction

Resources and the environment are the basis for human survival and development and the cornerstone of sustainable economic and social development. As China enters a new historical period, it needs to correctly understand the importance of the protection and utilization of arable land. Objectively analyze the problems existing in the protection and utilization of arable land, adhere to the concept of ecological protection and the concept of big food view, and make better use of the protection of arable land and the utilization of arable land to meet the demand for food and ecological and environmental protection, and then promote the modernization of China's agriculture.

The formulation of a coordinated development strategy in the context of ecological civilization aims to achieve an organic combination of ecological environmental protection and sustainable agricultural development in farmland construction and arable land protection policies [1-2]. The core objective of this strategy is to promote the coordinated development of agriculture and ecological environment in order to achieve economic, social and environmental sustainability [3-5]. In this strategy, focusing on ecological environmental protection, sustainable agricultural development, rural economic development, ecological civilization education and publicity, as well as policy support and regulation can provide strong support for achieving sustainable agricultural development and ecological environment protection [6-9]. Through the implementation of this strategy, it can promote the transformation of agricultural production methods, improve the efficiency and quality of agricultural production, and improve the living conditions of farmers, while protecting soil, water resources and biodiversity, realizing the benign interaction between agriculture and ecological environment, and providing a solid foundation for building a more prosperous and sustainable agricultural and ecological environment [10-14].

The implementation of the concept of ecological civilization into the protection of farmland is to plan the high-quality protection of farmland at the height of the harmonious coexistence of people and farmland [15-17]. Putting the protection of arable land in the overall layout of ecological civilization construction, it effectively promotes the ecological civilization and farmland construction to achieve coordinated protection in practice, improves the quality and stability of farmland ecosystems, and realizes the efficient synergy of farmland ecosystem services under the premise of ensuring the maximization of food production capacity [18-21].

Starting from the “three-in-one” arable land protection policy of quantity, quality and ecology, this paper realizes the design of arable land protection framework based on supply governance, control governance and empowerment governance. At the same time, this paper proposes a hybrid genetic algorithm integrating multi-objective genetic algorithm and PLS algorithm, which makes up for the shortcomings of multi-objective genetic algorithm in the local search, and thus improves the reliability of the land use optimization scheme with balanced development of economy and ecology, so as to realize the further reasonable optimization design of the framework of arable land protection.

2. Arable land protection framework in the context of ecological civilization

2.1. *Trinity policy for the protection of arable land*

Under the background of ecological civilization, the connotation of cultivated land protection has been continuously expanded, and the core goal of cultivated land protection has undergone the mission change of "dynamic balance of total cultivated land, permanent basic farmland protection, and recuperation system", and the cultivated land protection policy has shown a development and evolution process of "paying attention to quantity balance, paying equal attention to quantity and quality, and ecological trinity of quantity and quality".

The “trinity” protection system for arable land is shown in figure 1, and consists of policies for the quantitative, qualitative and ecological protection of arable land. The “trinity” protection system for arable land is not a simple patchwork of quantitative, qualitative and ecological protection of arable land; rather, it is based on a systemic concept that views quantitative, qualitative and ecological protection of arable land as an organic whole, and adheres to the independence and complementarity of the three, in order to strengthen the foundation of food security in all aspects.

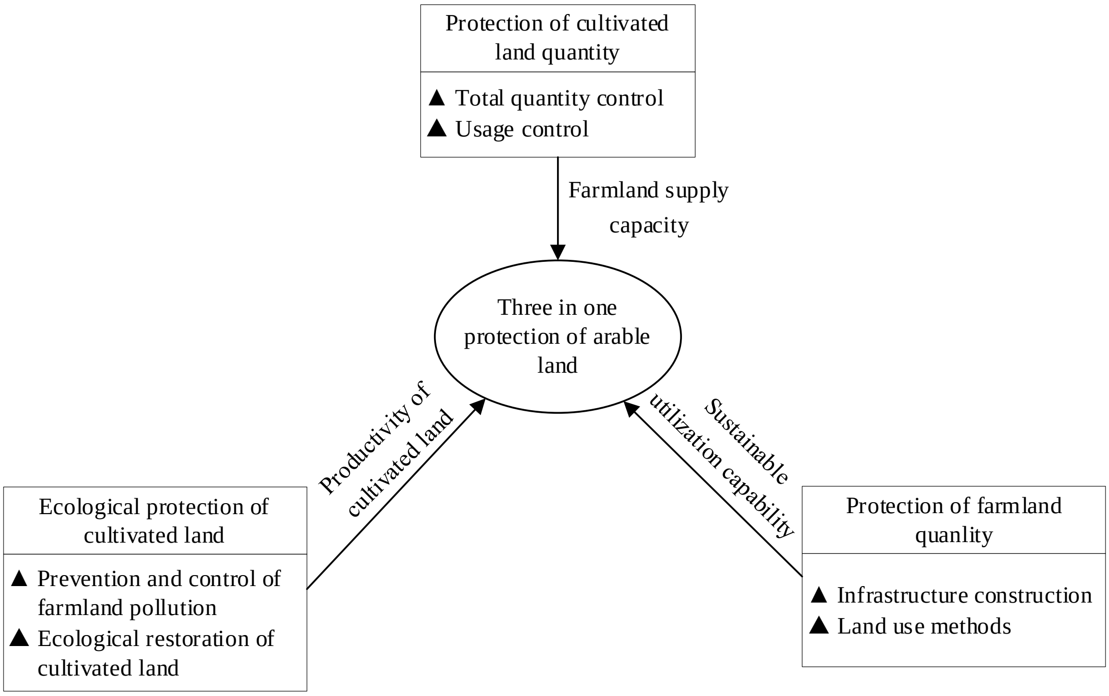

Fig. 1. The policy system of the "trinity" protection of cultivated land

Policies for the protection of the quantity of arable land include the realization of total quantity control and use control, with the aim of enhancing the supply capacity of arable land and ensuring that the total amount of arable land can meet the real needs of food security.

Policies to protect the quality of arable land include strengthening infrastructure construction and optimizing the use of arable land, with the aim of enhancing the production capacity of arable land and ensuring that food can be produced and supplied whenever needed.

Policies for the ecological protection of arable land include preventing and controlling pollution of arable land and promoting ecological restoration of arable land, with the aim of enhancing the ability to utilize arable land in a sustainable manner and ensuring the long-term stability of arable land's production capacity. Cultivated land pollution prevention and control focuses on “beforehand”, identifying potential risk points of cultivated land pollution and taking measures in advance to eliminate hidden dangers. Cropland ecological restoration focuses on the “aftermath”, repairing cropland that has already been damaged to minimize losses.

2.2. *Governance analysis framework for arable land protection*

The governance framework of arable land protection in the context of ecological civilization is shown in Figure 2, which is divided into supply governance, control governance and enabling governance.

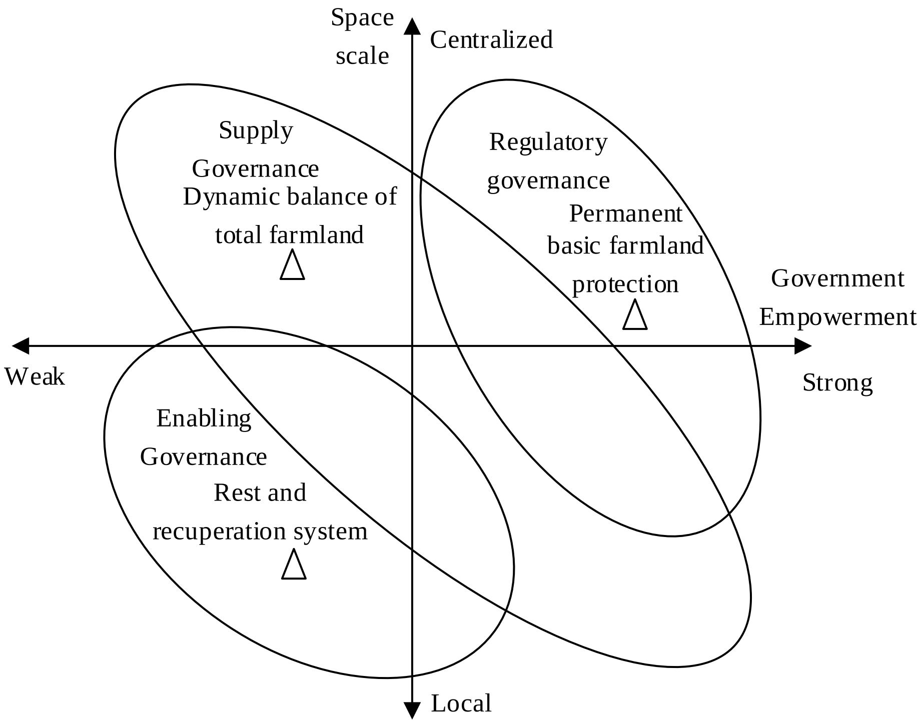

Fig. 2. The policy system of the "trinity" protection of cultivated land

The dynamic balance of the total amount of cultivated land is achieved by balancing the “demand” for land on which local governments plan and implement construction to occupy farmland with the “supply” of land on which they plan and implement construction occupation targets, in order to keep the amount of cultivated land unchanged, thus realizing early supply governance of cultivated land protection.

Permanent basic farmland protection is a strict control of arable land protection through the designation of high-quality farmland as permanent basic farmland in accordance with the law, which cannot be occupied or changed in use without authorization by any unit or individual, and the strengthening of social supervision so as to maintain the production capacity of food, thus forming a strict control governance of arable land protection.

The enabling governance-oriented arable land rest and recuperation system is based on the improved supply governance-oriented arable land occupation-supplementation balance and strengthened control governance-oriented permanent basic farmland protection as the cornerstone, and forms a synergy with the goal of implementing ecological civilization, which is an embedded governance that improves on the basis of the consistent arable land protection system. The embedded logic of cropland empowerment governance is shown in Figure 3.

On the one hand, it improves the “balance of occupation and compensation” that breaks through the governance of supply, keeps the quantity of arable land occupied and compensated without decreasing, and considers the path dependence of the reform of the protection policy. On the other hand, it strengthens the control governance of permanent basic farmland protection, improves the quality of permanent basic farmland, increases the comprehensive production capacity of food, and guarantees national food security. At the same time, the protection of arable land for rest and recuperation emphasizes “ecology”; on the one hand, the protection of arable land itself is the protection of ecology, and on the other hand, the protection of arable land quantity should not ignore the negative effects on ecology.

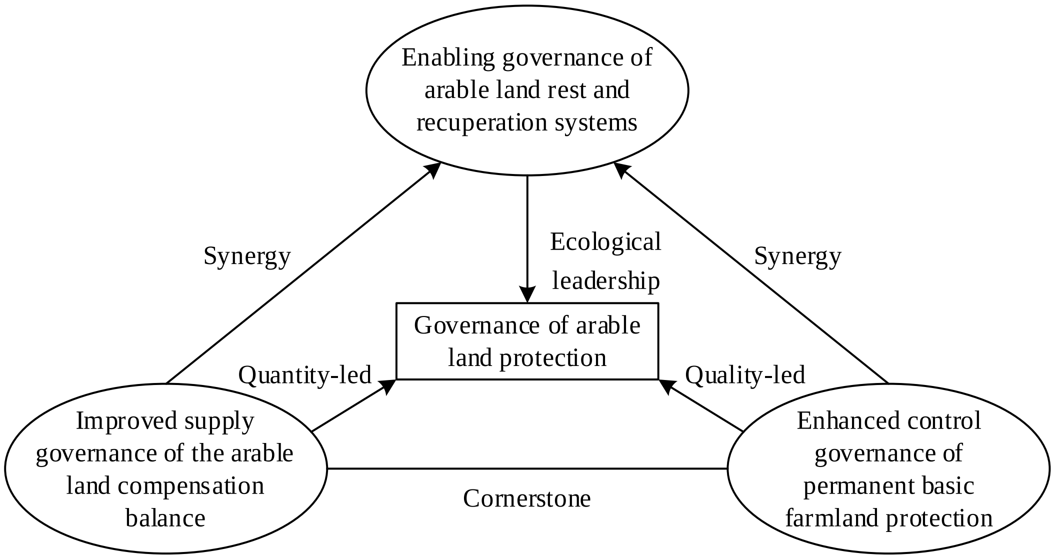

Fig. 3. Embedded logic of governance through enabling for cultivated land protection

3. Arable land protection model based on hybrid optimization algorithm

In this study, a hybrid optimization algorithm combining local search method and genetic algorithm is designed to optimize the policy, planning, implementation and supervision of arable land protection by combining the concept of ecological civilization. By constructing a multi-objective optimization model, the quantity, quality and ecological objectives in cropland protection are balanced to achieve the sustainable use of cropland resources.

3.1. *Multi-objective linear programming model*

3.1.1. Basic approach to multi-objective linear programming models. A multi-objective linear programming model consists of decision variables, objective function and constraints [22]. The general form of the model is:

$$\begin{gathered} opt\ z = f(x) \\ s.t. h_i(x) = 0, \quad \forall i \\ g_j(x) \leq 0, \quad \forall j \end{gathered} \tag{1}$$

Where: opt means optimize, which can be either Minimize or Maximize. $s.t.$ means "constrained by". $f(x)$ is the objective function, $h_i(x)$ and $g_j(x)$ are the constraint functions, and $\forall i$ and $\forall j$ are the number of constraints.

3.1.2. Multi-objective linear programming modeling for arable land protection:

1) Objective function. The problem to be solved by the optimization model is how much arable land can be retained to maximize the economic and ecological benefits of land resources within a certain number of years in the future.

2) Constraints. The constraints include the limitation of the total land area and the demand of each category of land in the national society and economy. The sum of each category cannot be more than the total land area. The constraints of the objective function and indicators are shown below:

The objective function is expressed as:

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} \omega_{ij} \left(\alpha_{ij} x_i \right) \tag{2}$$

Where: ω_{ij} is the weighting coefficient of each objective function. α_{ij} the benefit equivalents (economic, ecological, social) of the different sites. x_i is the decision variable. $i = 1, 2 \cdots 8$. $j = 1, 2, 3$.

Cultivated land constraints include food demand constraints and cultivated land supply constraints. The food demand constraint is expressed as:

$$x_1 \cdot R \cdot \varepsilon \cdot \eta \geq p \cdot \gamma \tag{3}$$

Of which: x_1 is arable land. R is grain yield. ε is the replanting index. η is the proportion of grain sown area in cropland. p is the food demand. γ is the food self-sufficiency rate.

Cropland supply constraint is denoted as:

$$x_1 \leq fl + pf + lc - ef - dd \tag{4}$$

Of which: fl is the area of current annual cropland. pf is the area of suitable agricultural reserve land. lc is the area of new cultivated land for land consolidation. ef is the area of ecological fallow land. dd is the area of disaster-damaged cropland.

Other agricultural land constraints are:

$$x_2 \geq pa \tag{5}$$

Where: x_2 indicates other agricultural land. pa is the other agricultural land in the current year.

The ecological balance constraints are categorized into ecological forest constraints, ecological grassland constraints and ecological watershed constraints. Among them, the ecological forest constraint is denoted as:

$$x_3 + x_4 \geq X \times \mu \tag{6}$$

Of which: x_3 is the area of garden land. x_4 is the area of forest land. X is the total amount of land. μ is the forest cover.

The ecological grassland constraint is expressed as:

$$x_5 \leq gl \tag{7}$$

Where: x_5 is the area of pasture land. gl is the area of pastureland in the current year.

The ecological watershed constraint is expressed as:

$$x_6 \geq tw \tag{8}$$

Where: x_6 is the area of pasture land. tw is the water area in the current year.

The economic development constraint is expressed as:

$$x_7 + x_8 \geq cl + tl \tag{9}$$

Of which: x_7 is the area of settlement and independent industrial and mining land. x_8 is the area of transportation land. cl is the area of settlements and independent mines in the current year. tl is the area of transportation land in the status quo year.

The unutilized land constraint is expressed as:

$$x_9 \geq nd \tag{10}$$

Where: x_9 is the area of other land. nd is the area of other land in the current year minus the area of developable land.

The total land area constraint is expressed as:

$$\sum_{i=1}^{9} x_i \le X \tag{11}$$

Of which: X is the total amount of land.

3.2. *Hybrid optimization algorithm design*

3.2.1. Simplex Algorithm. The basic idea of the simplex algorithm is: to construct an initial simplex with a given initial point and edge length, from this simplex, each iteration tries to construct a new simplex to replace the original simplex, so that the new simplex is constantly close to the minimal point of the objective function until the minimal point is searched for, the search of the simplex algorithm mainly consists of four kinds of operations: reflection, extension, contraction, and reduction of the prism length.

3.2.2. Genetic manipulation. In this paper, real number encoding is used, which makes the combination of genetic algorithm and simplex algorithm more natural and improves the efficiency of their fusion [23]. The crossover operator uses truncated crossover, which is a crossover operator similar to single point crossover in binary coding. The variation operator uses non-consistent variation, this operator searches the entire search space consistently at the beginning of the algorithm and locally at the later stages of the algorithm.

3.2.3. Design of the fitness function. Define the fitness function of Individual x as the weighted sum of the following m objective functions:

$$f(x) = \omega_1 f_1(x) + \cdots + \omega_m f_m(x) \tag{12}$$

Where: $\omega_i \ge 0$, $for\ i = 1, 2, \cdots, m$.

The aim is to find all Pareto optimal solutions, and to find different Pareto optimal solutions requires searching from different directions, in order to realize different search directions, the method of randomly generating weight vectors is used, i.e., the weight vectors are defined as:

$$\omega_i = \frac{random_i}{random_1 + random_2 + \cdots + random_m} \quad i = 1, 2, \cdots, m \tag{13}$$

where $random\, i(i = 1, 2, \cdots, m)$ is a randomly generated non-negative real number or non-negative integer.

3.2.4 Selection of operators. When selecting $N/2$ pair of parents for crossover operation, $N/2$ weight vectors are generated according to Eq. (13), and according to each weight vector a fitness function is constructed from Eq. (12), and a pair of parents is selected by each fitness function using proportions, which implies that if in one generation of genetic operation $N/2$ search directions are used, i.e., each selection is based on its own fitness function. The fitness function produced here will also be used for local search, so that both the genetic operation and the local search have many search directions.

When a pair of parents from the current population $X(t)$ is selected for crossover operation, m numbers $random_1, random_2, \cdots, random_m$ are first randomly generated, a weight vector $\omega = (\omega_1, \cdots, \omega_n)^T$ is computed according to Eq. (13), and the fitness function is computed according to Eq. (12), and the selection probability of each individual x in the current population is defined as:

$$P(x) = \frac{f(x) - f_{\min}(x(t))}{\sum_{x \in X(t)} \left(f(x) - f_{\min}(x(t)) \right)} \tag{14}$$

Where: $f_{\min}\left(x(t)\right)$ is the fitness of the worst solution in the current generation, i.e., $f_{\min}\left(X(t)\right)=\min\left\{f(x)\middle|x\in X(t)\right\}$. According to this selection probability, a pair of parents is selected from the current population $X(t)$.

When a pair of parents is selected, the crossover operator and the mutation operator are applied to this pair of parents in turn to generate two new individuals, and then a local search is carried out with these two new individuals as the initial points, respectively.The purpose of the local search is to make the generated new individuals better than the initial points, and so the direction of the local search follows the direction used in the selection of their parents.

When selecting a certain pair of parents from the current population $X(t)$ to be used in the crossover operation, the above operation needs to be repeated, i.e., a different weight vector is used for each pair of parents selected. Since the direction of the local search with a point x as the initial point is determined by the weight vector when selecting its parents, the selection operation and the local search have many directions.

3.3. PLS-based local optimization algorithm

PLS algorithms are mostly used in multi-objective optimization problems to explore around a certain individual in the population, in order to obtain a solution with better performance [24]. For the hybrid multi-objective genetic algorithm studied in this paper, local optimization algorithms will be introduced to make up for the lack of genetic algorithms in local search. In this paper, two Pareto-based local optimization algorithms will be proposed, IPLS local optimization algorithm for individuals and SPLS local optimization algorithm for ensembles.

3.3.1. Individual-based local optimization algorithm for IPLS. Whether an individual uses a local optimization algorithm in genetic multi-objective optimization is mainly determined by its individual performance, which is mainly determined by the utility value and its dominance. When the performance of an individual is poor, it is considered that there is a high probability that there are better individuals around it, and then it is necessary to explore its neighborhood in order to find a better solution.IPLS is an individual local optimization algorithm based on the idea of PLS algorithm, which is mainly used to improve the performance of the offspring after genetic operation, and the algorithm is used for local optimization only when the performance of the offspring is lower than that of the parent. Local optimization.

The IPLS algorithm consists of two important parts, neighborhood exploration and acceptance conditions. In the IPLS algorithm, when an individual explores a new individual solution in its neighborhood, it is accepted only if the new individual is not dominated by the original individual and satisfies the utility value less than the original individual. This acceptance condition setting is based on the following aspects:

1) In multi-objective optimization problems, especially when optimizing optimization problems with at least two conflicting objectives, the superiority of an individual cannot be determined by one of the objectives, and thus using dominance relationship only as an acceptance condition may explore the individual already obtained by the algorithm, when the local optimization does not have much meaning.

2) The important purpose of the IPLS algorithm is to improve the performance of the individual, when the newly explored individual has the same dominance relationship with the original individual, the purpose of local optimization is not achieved, so it is necessary to adopt the utility value as the acceptance condition while using dominance relationship, the smaller the value of utility the better the individual is, which ensures the local optimality of the IPLS algorithm.

3.3.2. Ensemble-based local optimization algorithm for SPLS. SPLS algorithm is an improved algorithm of PLS algorithm, which is to locally optimize the external population external elite population, but not all of the elements in the external elite population, but when the algorithm after each iteration, some elements from the external elite population are selected for local optimization. And the concept of hypervolume also known as hypercapacity is introduced into the SPLS algorithm to make up for the shortcomings of the algorithm in terms of evolutionary guidance ability. The good quality of a solution can be expressed by its hypervolume contribution, the set hypervolume is a measure of the size of the objective space dominated by a solution set, the larger the capacity, the better the quality of the solution set. And the hypervolume of a single solution is its contribution to the hypervolume of the entire solution set. According to the concept of hypervolume, also known as hypercapacity, it is only necessary to select the solution set whose individual contribution to the hypervolume is the largest for local optimization. The algorithm is improved in the following three main aspects:

1) Improving the selection strategy by adopting a selection strategy based on hypervolume, which guides the direction of local optimization according to the hypervolume of individuals.

2) Setting the number of updates for each element in the set, so that only the element whose number of times of local optimization is less than a threshold has a chance to be selected for local optimization, and once selected, the number of times it is used in the local optimization algorithm increases. One is because if a solution is selected for local optimization countless times, at that point it does not generate more new solutions and local optimization loses its meaning. Two, a solution is in its objective space. It may have no feasible solutions or very few solutions that are not dominated by it within a large hypervolume, because the solution is surrounded by only very sparse solutions, when it is generally assumed that it is surrounded by very searchable, i.e., there is a high probability of searching for the desired solution, and in order to put an end to this artifact an upper limit on the number of times of local optimization has been imposed. The updating strategy for the external population is improved by using a hypervolume penalization strategy.

First count the individuals in the external population P_{nd} whose number of local optimizations is less than the threshold "L", and denote by $\omega(a)$ the number of times an individual has been optimized. For each individual in the external population, count the number of individuals contained within the hypersphere centered on it, where the size of the hypervolume defined by each individual is the same, and denote by $\varphi(a)$ the number of individuals within the hypervolume of individual a.

$$\varphi(s)=\left|\left\{x\in P_{nd}\,\|\, f_i(s)-f_i(x)\right|\le\delta_i,\delta_i>0,i=1,2\ldots m\right\}\right| \tag{15}$$

Where: m is the number of objective components of a multi-objective optimization problem and δ_i is a positive real number measuring the size of the hypervolume. For a superspace of the same size, if an individual has a smaller value of $\varphi(a)$, it means that its space still has the potential to be explored, and if it is subjected to local optimization, the greater the possibility of exploring more optimal solutions, so the individual with a smaller value of $\varphi(a)$ is selected for local optimization. Let V be the M individual selected for local optimization ($M<N$ and N are the size of the external population).

For the acceptance criterion is the same as IPLS, for an individual a, if a new solution a' is explored in its neighborhood that is not dominated by the a and has a utility value lower than that of the individual a, the smaller the utility value the better its individual performance.

When some new individuals will be acquired after the local optimization algorithm has been used on the individuals in the external population, then updating the external population will be involved, because the external population involved in this paper is fixed. The updating of the external population adopts the update strategy based on hypervolume, specifically, when some new individuals want to enter into the external population, firstly, calculate their hypervolume value in the external population, in simple terms the hypervolume value is the size of the region of the target space dominated by the individual, and then delete the individuals with smaller hypervolume value from the external.

In the improved local optimization IPLS algorithm and SPLS algorithm, the acceptance criterion is improved, in addition to the use of non-dominated dominance relationship, but also additional utility value condition, the new explored individual is accepted only if the new explored individual is not dominated by the original individual and the utility value is less than the original individual. In multi-objective optimization problems, the function value obtained by Chebyshev's method is mostly used as the utility value of an individual, and the values of the components of the correlation vector of the objective value are set to be equal, which makes the calculation of the utility value computationally simple, but too dependent on the correlation vector. Therefore, the utility value is measured using the individual hypervolume, which is more objective to evaluate the performance of the individual. When using a local optimization algorithm for a specific optimization problem, it is necessary to define the neighborhood of an individual and its neighborhood exploration strategy.

3.4. *Algorithmic steps*

Step0: Preparation: determine the parameters of the genetic algorithm and local search.

Step1: Initialization, randomly select initial population.

Step2: Individual evaluation and updating of Pareto optimal solution temporary reservoir. For each individual in the current population calculate its function value for each objective function to update the Pareto optimal solution temporary reservoir.

Step3: Genetic operation, repeat the steps below step $\left(N-N_{elite}\right)/2$:

(1) Selection operation: randomly generate m random numbers, calculate the weight vector ω according to formula (13), calculate the fitness function according to formula (12), and select a pair of parents by proportional selection method according to the selection probability formula (14). (2) Crossover operation. (3) Mutation operation.

The $N-N_{elite}$ new individuals generated form the intermediate population $X'(t)$.

Step4: elitist strategy: randomly select N_{elite} individuals from the Pareto optimal solution temporary reservoir $P(t)$ to be added to the intermediate population $X'(t)$ generated by Step3, generating a local search initial point set $Y(t)$ containing N individuals.

Step5: Local search: each individual in the intermediate population $Y(t)$ is locally searched with local search probability P_l (the direction of the local search is determined by the fitness function when selecting its parent), and N new individuals are obtained, for which N new individuals are selected by the ratio of retaining the best individuals to N individuals to form the $t+1$th generation population $X(t+1)$.

Step6: Termination judgment: when the number of iterations reaches the pre-set maximum number of generations T, or the number of individuals in the Pareto Optimal Solution Temporary Reservoir $P(t)$ reaches the pre-set number of individuals M (here M is taken to be 500), the computation stops, and outputs each individual in the Pareto Optimal Solution Temporary Reservoir $P(t)$ as the Pareto Optimal Solution of the problem. Otherwise, set $t=t+1$ and go to Step2.

4. Multi-objective land use optimization based on arable land protection

In the optimization of land use structure, this paper takes 2050 as the planning year, and sets the natural development scenario based on the historical evolution trend and the "balanced economic-ecological" development scenario for comparative analysis. Firstly, the land use structure under the natural development scenario is obtained based on the historical land use data and Markov Chain prediction of the study area. On this basis, a multi-objective optimization model of land use is constructed based on the land use structure under the natural development scenario and the related planning data with the goal of maximizing economic and ecological benefits, and the multi-objective hybrid genetic algorithm is used to solve the problem of "economic-ecological equilibrium". The land use structure under the development scenario of "economic-ecological balance" is solved by multi-objective hybrid genetic algorithm.

4.1. *Current land use and natural development projections*

In this paper, based on the 2020 and 2023 land use vector data of County A, the land use transfer probability matrix from 2020 to 2023 is calculated as shown in Table 1.

Table 1. Natural development prediction of land use structure

In 2020	In 2023						
	Cultivated land	Garden land	Woodland	Grass	Construction land	Waters	Unused land
Cultivated land	0.993712	0.000010	0.000113	0.000006	0.006931	0.000014	0.000005
Garden land	0.000077	0.988754	0.000112	0.000003	0.011241	0.000005	0.000002
Woodland	0.000033	0.000007	0.999252	0.000010	0.001835	0.000002	0.000001
Grass	0.000043	0.000007	0.000237	0.997729	0.002109	0.000003	0.000006
Construction land	0.000185	0.000019	0.000061	0.000004	0.999710	0.000006	0.000003
Waters	0.000148	0.000015	0.000064	0.000004	0.004815	0.995146	0.000003
Unused land	0.000044	0.000006	0.000114	0.000015	0.001608	0.000001	0.998345

On the basis of Table 1, based on the principle of Markov Chain, MATLAB was used as the programming platform for programming, and 3a was used as a step to establish Markov Chain, and the program was run to predict to get the land use demand of the study area in 2050 under the natural development scenario based on the historical evolution trend. Setting seven decision variables such as cropland (x1), garden land (x2), forest land (x3), grassland (x4), construction land (x5), watershed (x6), and unutilized land (x7), and taking 2023 as the status quo year, the land use structure of the status quo in 2023 and the projected natural development in 2050 is shown in Table 2.

As can be seen from Table 2, forest land accounts for the largest proportion of the land use structure in County A in the status quo, 66.54%, followed by cropland, which accounts for 19.71%. By predicting the land use structure in County A under the natural development scenario, it can be seen that the share of cropland in 2050 will decrease the most, at 0.49%, and the shares of garden land, forest land, grassland and watershed will all decrease and be mainly converted into construction land (an increase of 0.78%).

Table 2. Natural development prediction of land use structure

	Variable	Current area in 2023/hm^2	Proportion	Natural forecast area in 2050/hm^2	Proportion
Cultivated land	x1	48437.26	19.71%	47244.43	19.22%
Garden land	x2	8103.32	3.30%	7788.82	3.17%
Woodland	x3	163542.62	66.54%	163151.74	66.39%
Grass	x4	8153.35	3.32%	8081.26	3.29%
Construction land	x5	10144.01	4.13%	12076.17	4.91%
Waters	x6	3817.19	1.55%	3765.24	1.53%
Unused land	x7	3563.49	1.45%	3653.58	1.49%

4.2. Optimization of land use structure for balanced economic and ecological development

In this paper, MATLAB is used as the programming platform, based on the constructed multi-objective optimization model of land use structure and hybrid genetic algorithm. The Pareto frontier solution of the land ecological benefit objective and economic benefit objective is obtained through several times of program tuning and comparison of results, and an optimal solution in the Pareto frontier solution represents a land use structure optimization alternative under the scenario of "balanced economic-ecological" development of County A in 2050. Optimization of land use structure in 2050 the distribution of Pareto non-inferior solutions based on multi-objective function is shown in Figure 4.

As can be seen from Fig. 4, the trend of the distribution of all the solutions shows that the two objective functions are significantly negatively correlated. From the definition of Pareto solution, it can be seen that there is no superiority or inferiority between the Pareto optimal solutions, and the decision maker can choose the most satisfactory solution according to his own experience and the importance of each objective.

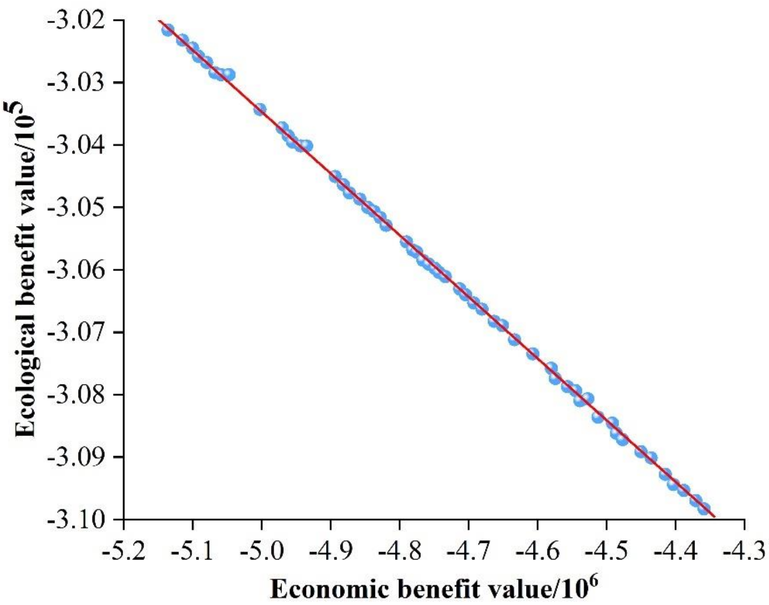

Fig. 4. Pareto non inferior solution front end distribution

Comparing different land use structure optimization schemes in the Pareto non-inferiority solution, it can be found that different schemes have different considerations for economic and ecological benefit objectives. In this paper, three typical schemes (balanced development of economy and ecology, economic dominance, ecological dominance) are selected from the Pareto non-inferiority solution for the next analysis and research, and the land use structure of the three typical schemes is shown in Table 3.

As can be seen from Table 3, between the 3 typical solutions, the difference between cultivated land, forest land and construction land is large, and the difference between garden land, grassland, water and unutilized land is small.

Scenario 2: This scenario mainly takes into account the economic benefits, as the cultivated land and construction land have high economic benefits, so the growth is larger, compared to the status quo in 2023, the cultivated land and construction land grow 651.37hm^2 and 2806.04hm^2 respectively, and the significant expansion of construction land will inevitably increase the oppression of the regional ecological environment, resulting in a corresponding reduction of forest land area by 2800.27hm^2.

Scenario 3: This scenario mainly takes into account the ecological benefits, so there will be a loss of economic benefits, compared with the status quo in 2023, the area of forest land increased by 2021.87hm^2, the area of arable land and the area of land for construction shrunk by 1,192.83hm^2 and 159.86hm^2, respectively.

Scenario 1: Compared with the status quo in 2023, the area of cultivated land increases by 184.06hm^2, which can maintain the total amount of cultivated land without decreasing and ensure the regional food security. Construction land grows by 1705.07hm^2, compared to Scenario 2, avoiding a significant expansion of construction land. The water area grows by 304.01hm^2.The forest land area is 162399.95hm^2, and the forest coverage rate is 66.08%, which indicates that the program ensures the stable development of regional ecological construction under the premise of reasonable limitation of economic development speed.

The land use structure of Scenarios 2 and 3 will lead to the imbalance of regional development, while Scenario 1 can realize the coordinated development of regional economic construction and ecological protection, therefore, this paper takes Scenario 1 as the optimization of land use structure under the scenario of "balanced economic-ecological" development of County A in 2050.

Table 3. Land use structure optimization alternative

	Solution 1 (Balanced development)	Plan 2 (Economic advantage)	Plan 3 (Ecological advantage)
Cultivated land (x1)	48621.32	49088.63	47244.43
Garden land (x2)	8105.46	8158.42	8046.34
Woodland (x3)	162399.95	160742.35	165564.49
Grass (x4)	7829.29	7804.61	7941.27
Construction land (x5)	11849.08	12950.05	9984.15
Waters (x6)	4121.2	4120.26	4123.09
Unused land (x7)	2834.94	2896.92	2857.47

The 2050 land use structure under the two different development scenarios and the changes compared to the current situation are shown in Table 4.

According to the land use pattern in 2023 under historical conditions, County A puts forward the requirement of stabilizing the forest cover at 65% in 2050. As can be seen from Table 4, because this paper adopts the multi-objective optimization method of balanced development of economy and ecology, the area of grassland and forest land after optimization is reduced compared with the natural development scenario. In the unoptimized scenario of natural development, the area of forest land is reduced by 0.24% compared with 2023, and the area of forest land is reduced by 0.70% after optimization, both of which satisfy the requirement of 65% forest cover. The optimized watershed area increases more compared to the natural development scenario. Compared to the water area in 2023, the water area of the natural development scenario decreases by 1.36%, while the optimized water area increases by 7.96%. Since the main factor considered in this optimized scenario is the coordination of economic and ecological benefits based on the protection of arable land, the area of arable land increases compared to the natural development scenario. Based on the evolution of historical conditions, the area of arable land in the original scenario decreases by 2.46% compared to the year 2023, whereas the optimized scenario increases by 0.38%, which is in line with the requirement of arable land retention. Regarding the change of building land, the proportion of building land increase decreases significantly due to the mutual requirements of cropland protection and forest land retention increase, and in the unoptimized scenario, the building land increases by 19.05% compared to 2023, while in the optimized scenario, the proportion of building land increase is only 16.81%. It can be seen that the regional economic development in the optimized scenario makes some concessions for the ecological environmental protection, and at the same time, due to the intensive economic development and industrial structure adjustment, the area of building land after the growth rate is slowed down is more in line with the requirements of the sustainable development of the economy and ecology in County A.

Table 4. Different development scenarios and changes in the use of soil

Land category	Area in 2023	In 2050					
		Natural development			Economic and ecological equilibrium development		
		Area	Variation	Variation ratio	Area	Variation	Variation ratio
Cultivated land	48437.26	47244.43	-1192.83	-2.46%	48621.32	184.06	0.38%
Garden land	8103.32	7788.82	-314.50	-3.88%	8105.46	2.14	0.03%
Woodland	163542.62	163151.74	-390.88	-0.24%	162399.95	-1142.67	-0.70%
Grass	8153.35	8081.26	-72.09	-0.88%	7829.29	-324.06	-3.97%
Construction land	10144.01	12076.17	1932.16	19.05%	11849.08	1705.07	16.81%
Waters	3817.19	3765.24	-51.95	-1.36%	4121.2	304.01	7.96%
Unused land	3563.49	3653.58	90.09	2.53%	2834.94	-728.55	-20.44%

4.3. *Analysis of the results of the optimization of the spatial layout of land use*

In this paper, the metacellular automata (CA) model is used to simulate the change of spatial layout of land use in County A. The model accuracy verification and simulation results are analyzed as follows.

4.3.1. Model Accuracy Verification. In this paper, the land use in 2023 is simulated based on the 2013 land use raster data using CA model, and each raster represents a tuple with a 3*3 Moore-type neighborhood. After many trials and selections, the random interference intensity of the random term is set to 2, and the transition probability threshold is 0.8. The land use situation in 2023 can be simulated after 10 iterations. According to the actual situation and simulation, the Kappa coefficient of this CA simulation is calculated, and the confusion matrix is shown in Table 5.

When the Kappa coefficient is within the interval of [0.60,0.80], it indicates that the simulation result is “very good”. As shown in Table 5, the Kappa coefficient of the confusion matrix of this simulation is 0.79, which is between 0.60 and 0.80, indicating that the simulation results meet the accuracy requirements.

Table 5. Confusion matrix of actual situation and simulation result in 2023

Land use type		Simulated area in 2023							Total/hm^2	Accuracy
		x1	x2	x3	x4	x5	x6	x7		
Actual area in 2023/hm^2	x1	46984.14	52.41	1133.8	77.14	65.76	102.54	21.47	48437.26	0.97
	x2	65.64	7941.25	42.25	20.34	11.03	9.57	13.24	8103.32	0.98
	x3	1158.24	104.78	162151.8	13.51	15.79	5.89	92.61	163542.62	0.99
	x4	41.31	3.12	11.42	8071.82	8.12	12.14	5.42	8153.35	0.99
	x5	84.23	32.34	11.42	21	9941.13	18.28	35.61	10144.01	0.98
	x6	17.43	10.09	4.85	4.17	1.45	3779.02	0.18	3817.19	0.99
	x7	18.12	11.94	3.35	0.93	0.14	1.15	3527.86	3563.49	0.99
Total/hm^2		48369.11	8115.93	163398.89	8208.91	10043.42	3928.59	3696.39	245761.24	
Accuracy		0.97	0.98	0.99	0.98	0.99	0.96	0.95		
Total accuracy		0.99								
Kappa coefficient		0.79								

4.3.2. Landscape pattern indices for CA simulation scenarios. Based on the theory of landscape ecology, this paper selects four indicators to analyze the spatial distribution characteristics of land use in the study area at the landscape level, including patch density (PD), which explains the degree of landscape fragmentation; the number of fractional dimensions (PAFRAC), which describes the complexity of patch geometry; the aggregation (AI), which describes the degree of patch discrete; and the Shannon Diversity

Index (SHDI), which reflects the degree of landscape fragmentation and heterogeneity. The landscape pattern index was calculated for the CA simulation scheme, and the results are shown in Table 6.

As shown in Table 6, from the PD of patch density, the overall patch density is 0.0857, indicating that the degree of fragmentation of various land classes is low. Among them, the highest patch density of construction land was 0.0341, indicating that the distribution of construction land was more fragmented compared to other land classes. From the landscape shape index PAFRAC, the landscape shape indices of cropland, garden land, forest land, grassland and construction land were larger, indicating that the shapes of these five land classes were more complex. From the aggregation index AI, cropland, woodland and grassland have higher aggregation indices than water, building land, garden land and unutilized land, indicating that cropland, woodland and grassland are more aggregated, which may be due to the fact that the three have larger areas, and therefore higher spatial aggregation compared to the other land categories. From the diversity index SHDI, the land use structure simulated by the CA simulation scheme has higher diversity and more reasonable spatial distribution. From the uniformity index, the land use structure simulated by the CA simulation scheme has higher diversity and more reasonable spatial distribution.

Table 6. Landscape Pattern Index of the Simulation result by CA

Land type	Cultivated land	Garden land	Woodland	Grass	Construction land	Waters	Unused land	Total
PD	0.0146	0.0122	0.0089	0.0161	0.0341	0.0098	0.0025	0.0857
PAFRAC	88.543	72.353	69.176	92.573	92.613	51.167	29.432	87.645
AI	75.286	45.213	71.165	56.359	39.426	41.218	38.794	64.784
SHDI								1.5326

4.3.3. Comparative analysis of landscape pattern indices. In order to verify the effectiveness of the hybrid genetic multi-objective model in performing land use optimization, this paper compares the optimal economic-ecological equilibrium scenario obtained from it with the status quo, CA simulation scenario in 2023 for the land landscape pattern index. The comparison results of the landscape pattern index are shown in Table 7.

As shown in Table 7, the patch density PD and shape index PAFRAC of the Pareto optimal scheme in this paper are 0.0825 and 87.026, respectively, which are smaller than the status quo in 2023 and the CA simulation scheme. And the aggregation index (AI=66.012) and diversity index (SHDI=1.5537) are greater than the 2023 status quo and CA simulation scenarios. This indicates that the optimized Pareto Option Set is less fragmented, more regular in shape, and more spatially clustered than the 2023 status quo and CA simulation scenarios, and the spatial layout of land use in the whole region is rationalized, and the distribution of each type of land is in a balanced trend in the overall landscape.

Table 7. Comparison of Landscape pattern index

	PD	PAFRAC	AI	SHDI
Status quo in 2023	0.0861	87.533	65.684	1.5278
CA simulation	0.0857	87.645	64.784	1.5326
Pareto optimal scheme	0.0825	87.026	66.012	1.5537

In conclusion, through the comparison of the target values of the Pareto economic-ecological balanced optimal scenario with the target values of the current land use status quo in 2023, the target values of the land use scenarios simulated by CA, and the comparison of the land landscape pattern indices of the various scenarios, it can be illustrated that the multi-objective model based on the hybrid genetic algorithm is feasible and effective in the optimization of land use. effectiveness, and the resulting set of scenarios not only meets the set objectives, but also has a higher degree of land use saving and intensification, and can also give decision makers a greater choice space, thus providing a reference for the design optimization of the existing arable land protection framework.

5. Conclusion

Taking County A as an example, this paper obtains the scenario preview of the optimal allocation of land use structure by constructing a multi-objective land use structure optimization model that weighs economic and ecological benefits and solving it by using hybrid genetic algorithm, so as to realize the optimization of the framework of arable land protection in the context of ecological civilization. The main conclusions are as follows:

1) Using multi-objective hybrid genetic algorithm to solve the problem of land use structure optimization allocation that satisfies different objectives such as economic benefits and ecological benefits, a set of Pareto non-inferior solution schemes can be obtained to make the comprehensive benefits reach a better level, which to a certain extent provides a variety of choices for the decision-maker's scenarios.

2) Due to the need to consider the protection of cultivated land and the construction of ecological civilization, taking into account the economic and ecological benefits, the optimization scheme, compared with the original scheme based on the evolution of historical conditions, the decrease of the area of woodland and grassland slightly increased, the decrease of the area of woodland changed from 0.24% to 0.70%, and the area of grassland changed from 0.88% to 3.97%, but it can still relatively satisfy the requirements of the policy. On the other hand, the area of water area has increased greatly, from -1.36% in the original proposal to 7.96% in the optimized proposal, giving full play to the role of wetlands in ecological nourishment. At the same time, the cultivated land has a bigger change than the original scheme, increasing from -2.46% to +0.38%, which meets the requirement of cultivated land retention.

3) The patch density PD, shape index PAFRAC, aggregation index AI, and diversity index SHDI of the Pareto optimization scheme in this paper are 0.0825, 87.026, 66.012, and 1.5537, respectively, the first two of which are smaller than the status quo and CA simulation scheme in 2023, and the latter two are larger than the status quo and CA simulation scheme in 2023. It indicates that the optimization scheme obtained in this paper has reduced fragmentation, more regular shape and higher spatial agglomeration compared with the 2023 status quo and CA simulation scheme, and the spatial layout of land use of the whole region develops towards rationalization, and each type of land is distributed in the overall landscape with a balanced trend.

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